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Digital Architecture Design and Implementation for Performance Optimization of Electromechanical-Hydraulic Systems: A Case Study on Injection Molding Machines

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Abstract.

Performance degradation under temperature rise conditions is a persistent challenge in the motion clamping system of injection molding machines, where unmeasurable variations in oil viscosity led to pump efficiency loss and positioning accuracy deterioration. To address this issue, this study proposes a platform-assisted approach for system performance modelling and control optimization. A digital platform integrating data acquisition, simulation analysis, and data review is developed to enable unified analysis of measured operating data and model predictions. Using the temperature-dependent viscosity effect as a representative case, a data-driven inverse identification method is implemented through platform-based parameter mapping and implicit indicator extraction, allowing an engineering-oriented redefinition of leakage characteristics in the pump flow model and explicit incorporation of the viscosity-temperature relationship into system modelling. Based on the established model, a pump flow compensation channel is introduced into the original position-based PID control architecture to provide feedforward correction for temperature-induced flow degradation. Experimental results under multiple operating conditions demonstrate that the proposed method significantly improves positioning accuracy and control consistency. The study provides an effective modelling and control optimization framework for performance degradation driven by unmeasurable latent variables in electromechanical-hydraulic systems.

Keywords. Electromechanical-hydraulic systems; Digital technology architecture; Digital platform; Performance optimization; Injection molding machine

1. INTRODUCTION

In recent years, digital twins and digital prototypes have attracted increasing attention in both industry and academia, with digital technologies emerging as a key driver for overcoming existing limitations and enabling transformative upgrades [1]. In equipment manufacturing in particular, digital technologies—leveraging production data as a central link—have introduced new models and methods across all stages of production, significantly advancing the industry toward higher efficiency, intelligence, and sustainability [2, 3].

Electromechanical-hydraulic (EMH) systems are the core driving units of industrial equipment, with their performance directly determining functional value across the entire life cycle. FIGURE 1.1 shows the key stages from development to decommissioning, among which the performance tuning stage plays a pivotal role in optimizing the preliminary prototype into a high-performance product. However, the multidisciplinary coupling of EMH systems introduces substantial challenges in both forward design and reverse debugging of industrial equipment [4].

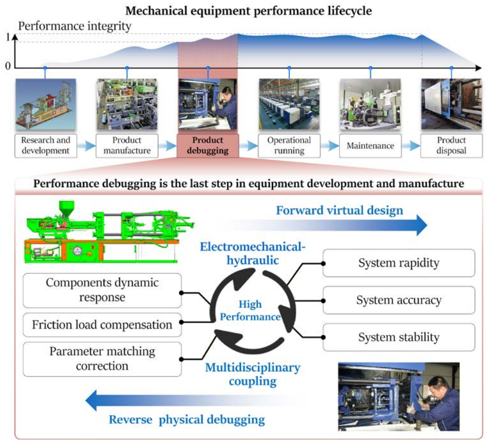

Figure1.1. Equipment Lifecycle and Performance Debugging Phase

1.1. Industry Status and State of the Art

First, the dynamic responses of multidisciplinary components are inconsistent, and complex parameter matching makes it difficult to accurately predict operating performance at the design stage [5]. Meanwhile, nonlinear factors such as friction and inertial loads increase uncertainties in debugging, compromising system stability and responsiveness [6]. Moreover, conventional debugging relies heavily on manual experience [7], with limited data integration, poor documentation, and weak knowledge reuse, which constrain efficiency and global optimization [8]. Therefore, introducing digital technologies, virtual debugging, and intelligent methods is essential to optimize the process, shorten the cycle, and ensure accurate and efficient EMH system debugging [9].

Currently, research on digitalization and platform construction is emerging across equipment design, debugging, manufacturing, and operation and maintenance [10–13]. Within debugging, studies focus on assembly debugging, which verifies functional integrity, and performance debugging, which optimizes operational performance. In various industries, digital technologies have partially addressed key challenges, including variable operating conditions [14], conflicts between development cycle and quality [15], high costs [16], equipment discreteness [17], complex and error-prone design processes [18], and strongly time-varying performance indicators [19]. However, for complex EMH equipment, application cases remain limited, and substantive support is lacking.

This study focuses on the EMH system of an injection molding machine (IMM) and addresses the demand for motion accuracy optimization of the motion clamping system (MCS) by proposing a performance tuning–oriented digital system architecture. The proposed architecture consists of a physical layer (PL), a simulation layer (SL), a data relay layer (DRL), and a visualization layer (VL), and establishes a data visualization workflow for system diagnosis and optimization based on high-fidelity multidisciplinary models. The PL corresponds to the actual IMM system. The DRL enables real-time acquisition and updating of multiple key operating variables using a limited number of sensors. The VL serves as the human-machine interface, providing the display of diagnosable variables and supporting performance analysis. The SL implements virtual sensing through multidisciplinary simulation to characterize both dynamic and static system behaviours, conduct coupled multidisciplinary analyses, and virtually estimate implicit parameters that are difficult to measure directly. In this way, the proposed architecture reveals both explicit and implicit factors affecting system performance, thereby improving system tunability and motion accuracy.

2. OVERALL DESIGN OF SYSTEM ARCHITECTURE

2.1. Overview of the MCS of the IMM

The research object—MCS of an IMM—is a core unit of plastic forming. It must travel about 1 m within 1 s, maintaining millimeter-level positioning while withstanding high-speed motion of mold components weighing several tons. The system operates via motor-driven hydraulic pumps that actuate the MCS. System configuration and motion accuracy are shown in FIGURE 2.1. Scatter plots indicate that actuator motion raises hydraulic oil temperature and positioning errors. High inertia, rapid response, and strict precision requirements pose severe challenges to conventional commissioning methods.

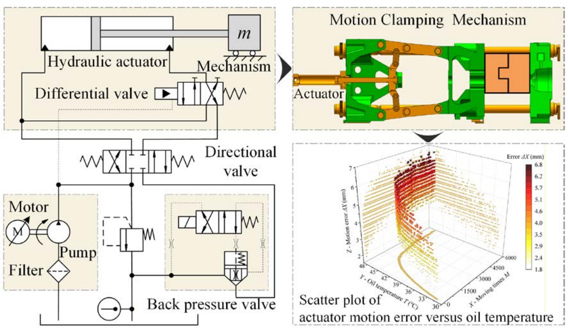

Figure 2.1. The EMH System of IMM and Its Existing Problems

2.2. Requirement Analysis

Based on the overview and current challenges of the MCS, the logical relationships of the requirements in the context of digital upgrading are illustrated in FIGURE2.2 and can be summarized as follows:

(1) High-precision simulation models: Digitalization requires high-fidelity models that accurately map physical entities. Incorporating external, inertial, and frictional forces enables faithful reproduction of the platen's dynamics. Such models allow analysis of operational deviations, and support improvements in motion accuracy and stability.

(2) Feature data support: The MCS requires a data acquisition system to collect and process key state data, enabling the simulation model to accurately depict equipment operation.

(3) Visualization platform: The platform integrates simulation models with the data acquisition system, providing intuitive display of real-time states, trends, and implicit variables to enhance system transparency, while offering interactive interfaces for functional expansion and optimization analysis.

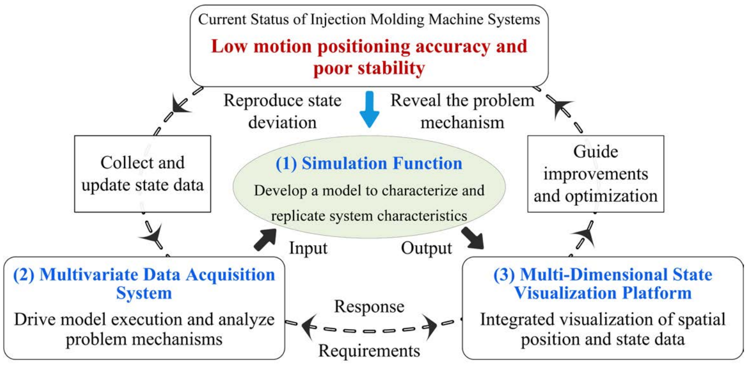

Figure2.2. Digital Technology Application Requirements for the MCS of the IMM

2.3. Architectural Design

Based on the aforementioned logical relationships of requirements, a digital application scheme is designed, encompassing both functional hierarchy design and technology framework design.

(1) Functional Hierarchy Design

This study follows an application-driven and incremental digitalization paradigm, rather than pursuing a fully instantiated, end-to-end global digital twin in a single step. Based on the current state and requirements of the MCS, the digital upgrade should adopt a four-level architecture: physical entity, system model, multi-source data acquisition system, and visualization platform. The following sections define each level and its objectives.

① PL: The MCS provides geometric and state data, forming the dynamic basis of the digital architecture. This layer includes components and sensors for data acquisition.

② DRL: This layer collects and manages multi-source data between the physical entity and digital space, serving as the core medium for their interaction. It includes transmission systems, protocols, and databases to enable efficient data transfer, storage, and management.

③ SL: Integrating the physical system's geometric and state models with its operational logic, this layer creates a virtual representation of the entity. Using data from the DRL as constraints, it replicates EMH system operation, serving as the core of digital applications.

④ VL: Serving as the interface between the physical entity and simulation model, this layer manages data acquisition, simulation execution, and comparative analysis of physical and simulated states. By identifying optimization parameters, it enhances the application of high-precision SL models, providing intuitive support for performance analysis and optimization.

(2) Technical Architecture Design

The above four functional levels establish a digital application framework for the MCS, centered on a high-precision simulation model. On this basis, it is necessary to further develop operational logic and implementation standards to form a complete digital technology architecture, which can guide system application and deployment. This technology architecture is shown in FIGURE2.3.

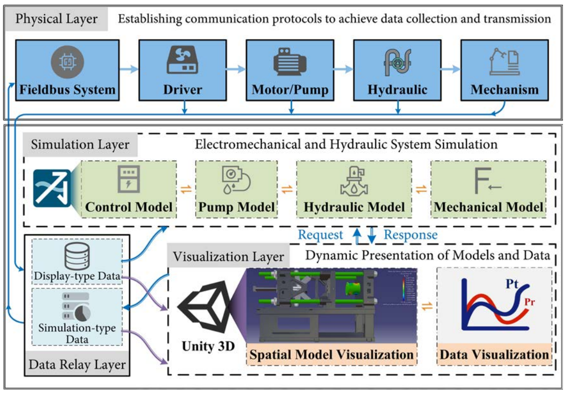

Figure 2.3. Digital Application Technology Architecture of the MCS

Based on this technology framework, the system operates as follows: During the operation of the MCS, the VL monitors system performance and collects state data for computation in the SL and for visual display. The acquired data and simulation data are synchronously stored in the DRL, supporting dynamic comparison and subsequent analysis on the VL. By linking all layers through data, the framework drives the high-precision simulation model to reproduce motion deviations in the MCS. The state variables in the model are abstractly represented on the VL, and through explicit comparison of observable states and implicit calculation of latent states, the system's operational mechanisms are revealed, providing guidance for optimizing motion positioning accuracy in the MCS.

3. DIGITAL PLATFORM DEVELOPMENT

This section builds a performance optimization digital platform for the MCS based on the proposed digital application technology architecture. By integrating multidisciplinary simulation, data flow processing, and visualization technologies, the platform enables the digital upgrade of the debugging process.

3.1. SL Construction

Multidisciplinary co-simulation is essential for the study of EMH systems. By characterizing the interactions among multiple physical fields, it reveals the system's dynamic behaviour and coupling effects, providing theoretical support for optimization. In this study, a hierarchical modelling strategy is employed to construct the SL for the MCS.

(1) Mechanical Structure Model

As the actuator of the system, the MCS is required to achieve precise positioning, rapid dynamic response, and continuous coordination across multiple motion stages during operation. However, latent factors such as component deformation, coupled inertial effects, and friction exert a significant influence on its dynamic performance. To address these issues, this study proposes a symmetric recursive method based on Newton–Euler dynamics and introduces a deformation allocation strategy grounded in the ratio of component stiffness coefficients. By exploiting measurable displacement variables, unmeasurable parameters, including coupled inertia and structural deformation, are inferred, enabling the construction of explicit dynamic models for sub-stages. This framework facilitates virtual sensing and thereby enhances the observability of the motion process.

In addition, an equivalent friction modelling approach is adopted to provide a unified representation of friction effects arising at multiple positions and governed by different friction mechanisms. A position–pressure dual-parameter identification and switching logic is further developed, enabling the establishment of a dynamic model that spans the entire operational process of the mechanism. Experimental results demonstrate that the accuracy of each stage-specific sub-model exceeds 90%, while the overall model accuracy remains stably above 97% under continuous multi-cycle operating conditions, thereby achieving high-fidelity dynamic simulation of the MCS throughout its full process. Detailed procedures and analyses of the related study can be found in Ref. [6].

(2) Hydraulic-Electro-control Model

The electrohydraulic control subsystem is characterized by numerous components and complex parameter coupling. During the research process, model development is often constrained by practical factors such as industrial confidentiality arising from market competition, non-standardized designs, and the difficulty of directly measuring fluid parameter characteristics, which together pose significant challenges to accurate modelling. To address these issues, this study integrates multiple approaches: characteristic curves relating rotational speed to volumetric efficiency and torque based on performance and efficiency samples for the pump; component disassembly, inspection, and dimensional measurement of spool geometry and spring stiffness for the directional control valve; and black-box principle-based validation for the back-pressure valve. By fully accounting for multidisciplinary coupling, as well as nonlinear effects such as temperature, viscosity, and friction, electrohydraulic control subsystem models of the MCS are established.

(3) Integrated Model

Since the MCS couple mechanical, hydraulic, and electrical domains, this study develops an integrated EMH model based on existing subsystems. By coupling these models, a unified multi-domain dynamic simulation platform is established. Here, the electro-control model issues motion commands to the hydraulic model, which simulates pressure and flow and drives the mechanical structure. As the actuator, the mechanical structure feeds back displacement, velocity, and acceleration, enabling the electro-control system to adjust parameters accordingly. The approach, model, and results are shown in FIGURE3.1.

3.2. DRL Construction

Based on the proposed technology architecture, this section elaborates on the construction of the DRL from three aspects: data acquisition, data storage, and data-driven applications.

(1) Data Collection

Data acquisition should be based on the EMH mechanism model of the MCS, in order to identify key parameters and thereby determine the types of data required. These data encompass three aspects: mechanical, hydraulic, and electro-control, as detailed below:

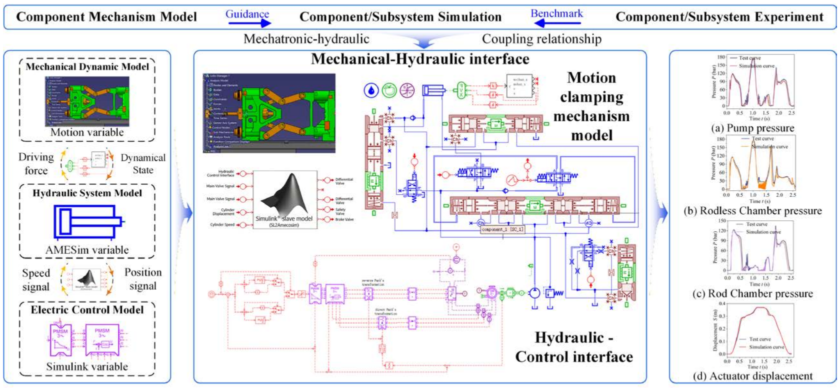

Figure3.1. EMH Combined Simulation Model of the MCS

(1) Mechanical part: Focus on monitoring the displacement-acceleration mapping relationship between the input and output ends of the MCS, as well as the deformation of tie bars, in order to calculate the clamping force and analyse the effects of inertia, friction, and deformation on the system.

(2) Hydraulic part: Monitor the inlet and outlet pressures and flow rates of each hydraulic component to evaluate the effects of hydraulic losses, cavitation, and pressure build-up processes on system performance. Meanwhile, a combined pressure–temperature sensor is installed at the return port of the hydraulic oil tank to enable real-time monitoring of the oil temperature, thereby revealing the intrinsic relationship between temperature rise and performance degradation.

(3) Electro-control part: Monitor motor speed, torque, and solenoid valve enabling signals to analyse the impact of signal delays on system performance.

Considering the diversity of data types, the dispersion of measurement points, and the stringent requirements on transmission cycle and sensitivity, this study employs a fieldbus motion control unit based on the EtherCAT communication protocol as the master-slave transmission device, enabling efficient acquisition and integration of multi-source data. In addition, the Modbus TCP protocol is used to facilitate data and command interactions between the fieldbus system and the host computer platform. Ultimately, a multi-source data acquisition and interaction system is established, in which the fieldbus system serves as the relay, with EtherCAT and Modbus TCP protocols operating collaboratively, as illustrated in FIGURE 3.2.

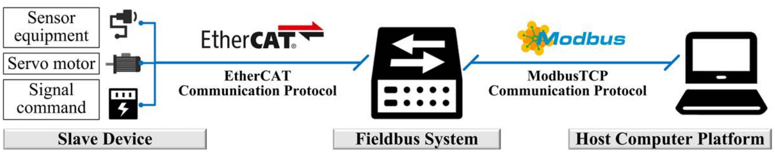

Figure 3.2. Multi-Source Data Acquisition and Interaction System

The real-time performance of data updates is a key indicator of system performance. In this study, the system communication delay was measured to be approximately 50 ms. Compared with the 2.3 s cycle of continuous motion tests and the production operation cycles exceeding 10 s, this delay has a negligible impact on the performance of the digital platform, thereby ensuring the reliability of real-time data interaction.

(2) Data Storage

Efficient data storage and management directly affect the operational efficiency of the digital platform. In this study, system data are categorized into display data and simulation data, and hierarchical storage is implemented using MySQL, with Navicat employed for management.

① Visualization Data: This includes system test and simulation data, encompassing system state parameters such as actuator displacement, clamping force, and component pressures and flow rates, and is primarily used for monitoring and result visualization.

② Simulation Data: This involves the modelling parameters of individual components and the system simulation model, such as spool diameter and damping, which serve as inputs for model computation and simulation analysis.

To enable convenient "one-click simulation" functionality and support comparative analysis of multiple data types, this study integrates a MySQL database communication interface within the Python simulation scripts, allowing for automatic storage and visualization of simulation results. To address the comparative debugging requirements of step-type components, a component parameter modification window was added (see Section 4), supporting parameter adjustment and simulation analysis for components of different specifications, thereby enhancing the flexibility and specificity of performance tuning.

(3) Data Drive

The key to achieving digital-assisted debugging of the MCS lies in the platform's ability to call and drive multi-source data and simulation models, transforming simulation results into visualized optimization guidance and gradually realizing virtual debugging. As shown in Figure 3.3, this study connects the multidisciplinary simulation software AMESim via a software interface, utilizing Python scripts to drive simulation execution while interacting with the database. The specific process is as follows:

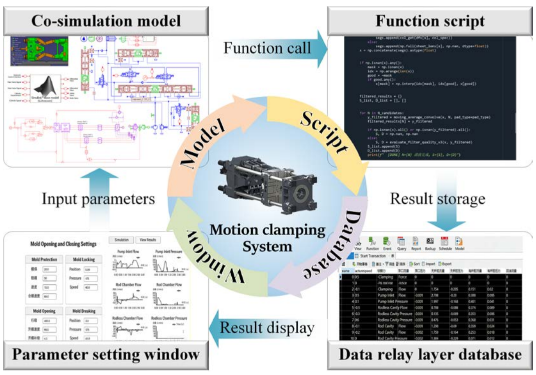

Figure 3.3. Platform-Driven Integrated Simulation Framework Logic

① Parameter Modification: Users adjust component parameters via the platform interface, and the modified data are written to the database through data communication.

② Simulation Execution: The script calls the AMESim simulation model, retrieves the updated parameters from the database, and drives the simulation computation.

③ Data Storage: During simulation, the model dynamically references parameter variables from the database, and upon completion, the results are stored in the database.

④ Visualization Display: The platform retrieves the simulation results and presents them intuitively through the Unity interface, enabling full-process visual interaction for parameter adjustment, simulation execution, and result review.

It is worth noting that the proposed DRL is designed to be protocol-agnostic. Given the widespread use of EtherCAT and Modbus TCP in industrial environments, these protocols are adopted in this study, while the relay layer abstracts raw data into unified data objects. This design enables higher-level industrial communication standards, such as OPC UA, to be integrated as gateway or middleware solutions without affecting the proposed modelling and control optimization approach.

3.3. VL Construction

The VL, serving as the carrier for both the SL and the DRL, not only supports the MCS and integrated data management but also acts as the interface for the digital platform's functional output. This section describes the construction of the VL from three aspects: functional positioning, architecture, and operational logic.

(1) Platform Functionality Positioning

Within the context of achieving virtual equipment commissioning, the platform's functional positioning encompasses three core functions:

① Status Monitoring: Utilizing a 3D model of the IMM in combination with data communication technology, the platform synchronously mirrors the physical system, dynamically presenting the operational process and spatial states of the MCS.

② Virtual Commissioning: Leveraging the simulation model and measurable parameters of the EMH system, the platform maps unmeasurable variables to potential system performance, thereby enhancing transparency in system debugging.

③ Data Management: The platform provides efficient and intuitive data query and analysis capabilities, supports historical data retrieval, and integrates comparative analysis of experimental and simulation data to reveal underlying patterns in system parameter variations, offering a foundation for optimization decisions.

(2) Platform Architecture

Based on the functional positioning, the DRL includes display data and simulation data. Display data are connected to the data acquisition system through experimental data communication, enabling data integration and storage. Simulation data rely on software interfaces to establish communication between the SL and scripts, supporting co-simulation of the MCS, storing computation results, and facilitating comparison between experimental and simulation data.

The status monitoring function maps physical entity data to the experimental data layer via data communication, ensuring synchronous updates between the VL and the PL and enabling intuitive monitoring of system states. The virtual simulation function allows parameter adjustments through the platform and visualizes simulation results, providing support for system optimization. The data management function integrates experimental and simulation data, facilitating data comparison, trend analysis, and optimization decision-making on the platform, thereby enhancing the tunability and optimization capability. The development environment and tools used in this study are listed in TABLE3.1.

Table3.1. Digital Platform System Development Environment and Tools

Item	Describe
Operating System	Window10
Programming Language	C#, Python2.7.15
Open-Source Tool	Numpy, Matplotlib
Database	My SQL8.0, Navicat
Visualization Tool	Unity3D, 3Ds Max, Xchart

4. PLATFORM-ASSISTED MODELING AND CONTROL OPTIMIZATION

This section presents the functional modules of the platform developed based on the aforementioned architecture and, taking the MCS performance degradation induced by oil temperature rise shown in FIGURE 2.1 as a case study, verifies the effectiveness of the proposed technical architecture in system diagnosis and performance optimization.

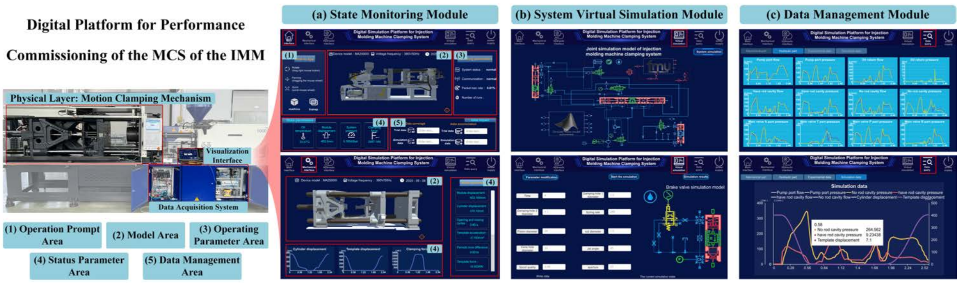

Figure 4.1. Digital Platform Interface of the MCS of IMM

4.1. Platform Functions

The platform takes the MCS as the research object and, through multi-level modelling as well as parameter interaction and analysis, realizes visual representation of system operating states, online evaluation of key parameters, and closed-loop support for the design and commissioning processes, thereby providing a unified tool environment for performance degradation diagnosis and validation of optimization strategies. The overall interface of the platform is shown in FIGURE 4.1.

(a) *State Monitoring and Visualization Function*

The platform integrates state monitoring functions at the system, mechanical, and hydraulic levels. Through the coordinated visualization of three-dimensional models and parameter panels, the operating state of the equipment is presented in an intuitive manner. During system operation, key parameters such as oil temperature, platen displacement, system pressure, and clamping force are updated in real time and synchronously displayed with the motion process. At the mechanical level, the platform directly reflects state variations of the MCS, while at the hydraulic level, dynamic schematic diagrams illustrate hydraulic circuit switching and actuator actions. This enables comprehensive perception of the multi-physical states of the EMH system, providing an intuitive basis for operating condition assessment and anomaly identification.

(b) *System- and Component-Level Virtual Simulation Function*

The platform adopts a hierarchical virtual simulation architecture, enabling parametric simulation and result analysis at both the system and component levels. Based on the system model, users can adjust key component parameters and trigger corresponding simulation calculations, with the simulation results fed back to the platform in real time for performance evaluation. This functionality establishes a rapid mapping between variations in component parameters and the dynamic response of the system, providing an efficient virtual validation approach for structural design, parameter matching, and performance tuning.

(c) ***Data Management and Comparative Analysis Function***

The platform incorporates a unified data management module that enables centralized storage, retrieval, and comparative analysis of experimental and simulation data. Users can access historical data by operating cycle and perform synchronized comparative visualization of multiple categories of system parameters to reveal performance differences under varying operating conditions or parameter configurations. By supporting visualization of multiple physical quantities across multiple coordinate axes, the platform significantly enhances data interpretation efficiency, providing robust data support for system performance degradation analysis and optimization decision-making.

4.2. Optimization Support Based on the Digital Platform

Conventional performance tuning of the MCS in IMM primarily relies on an offline trial-and-error process driven by human experience. This process typically takes directly measurable explicit performance indicators, such as cylinder displacement error and system pressure response, as references, and compensates for performance degradation caused by changes in leakage characteristics, evolution of friction behaviour, and deterioration of actuator dynamic response during long-term operation by repeatedly adjusting parameters including control loop gains, pressure thresholds, or servo pump speed limits. However, this tuning approach is essentially an experience-based correction method relying on outcome feedback, and its effectiveness is highly dependent on the subjective judgment of the operator. In particular, for key influencing factors that are difficult to measure online, their effects can only be indirectly reflected through system-level performance degradation, making it challenging to distinguish whether observed performance variations originate from improper control parameter settings or from the evolution of component intrinsic characteristics under varying operating conditions. As a result, a clear causal mapping between parameter adjustments and system responses is lacking. Owing to these limitations, traditional manual tuning is often characterized by long commissioning cycles and poor reproducibility of parameter settings, and it provides limited support for subsequent mechanism analysis, model refinement, and performance optimization.

This study takes the empirically observed phenomenon of system performance degradation induced by variations in hydraulic oil temperature as the starting point. By combining theoretical derivation and analysis with the mapping capability of a digital platform, a quantitative relationship is established between the viscosity-temperature characteristics of the hydraulic oil, the leakage behaviour of the gear pump, and the corresponding flow equations. On this basis, explicit characterization of pump efficiency variations and the development of a corresponding compensation model are achieved.

As the core driving unit of a servo pump-controlled system, the hydraulic pump plays a decisive role in overall system performance, and its internal leakage is one of the primary factors leading to performance degradation, which is commonly characterized by the pump volumetric efficiency. Owing to the compact structure of gear pumps, the dynamic microscopic clearances and the associated leakage paths that vary with operating conditions are difficult to measure directly using conventional methods. Therefore, this study adopts an experimental data–driven parameter inverse identification approach to systematically test and model the efficiency characteristics of the pump under different oil temperature, pressure, and rotational speed conditions. Specifically, based on the developed digital platform, multi-condition experimental data and the corresponding simulation results are managed in a unified manner and visualized synchronously. By aligning and analysing key variables such as pump outlet flow rate, pressure, and rotational speed, and by minimizing the discrepancy between experimental measurements and model outputs, the key parameters related to internal leakage in the flow rate equation are inversely identified. In this way, a quantitative mapping between pump performance indices and theoretical model parameters is established. Consequently, the flow rate equation of the engineering-oriented internal gear pump can be redefined as:

$$Q_{\mathrm{a}} = v_{\mathrm{c}} n_{\mathrm{p}} \cdot \left[1 - \frac{C_{\mathrm{leak}} \cdot \Delta p}{\mu(T) \cdot v_{\mathrm{c}} n_{\mathrm{p}}} \right] \tag{4.1}$$

where, Q_a denotes the actual output flow rate, v_c is the constant displacement of the pump, n_p represents the actual rotational speed of the pump, Δp is the pressure difference between the high-pressure and low-pressure chambers, μ(T) denotes the dynamic viscosity of the hydraulic oil as a function of temperature, and C_{leak} is the fitted leakage coefficient.

The volumetric efficiency of the pump can then be defined as:

$$\eta_{\mathrm{v}} = \frac{Q_{\mathrm{a}}}{v_{\mathrm{c}} \cdot n_{\mathrm{p}}} = 1 - \frac{C_{\mathrm{leak}} \cdot \Delta p}{\mu(T) \cdot v_{\mathrm{c}} n_{\mathrm{p}}} \tag{4.2}$$

Equation (4.2) indicates that the pump's flow delivery capability is primarily influenced by the combined effects of rotational speed n_p, hydraulic oil viscosity μ(T), and pressure differential Δp. Among these factors, the temperature-dependent evolution of oil viscosity is difficult to measure directly and represents a key source of uncertainty affecting the accuracy of pump volumetric efficiency estimation. To address this issue, the digital platform was employed to uniformly collect and manage system operating data for the hydraulic oil used (ISO VG 46) under varying temperature conditions. A parametric model of the relationship between oil viscosity and temperature was then developed, yielding an exponential viscosity-temperature empirical correlation, as shown in FIGURE 4.2 When this viscosity-temperature model is explicitly embedded in the controller, the current oil viscosity can be continuously estimated based on real-time readings from a temperature sensor, and, in combination with Equation (4.2), the pump volumetric efficiency η_v can be calculated and compensated online.

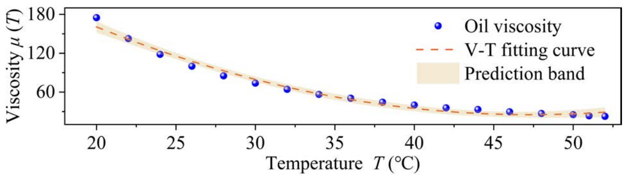

Figure 4.2. Viscosity-temperature fitting curve of hydraulic oil

4.3. Platform Performance

By integrating the oil viscosity–temperature model into the controller, this study introduces a pump flow compensation channel based on the viscosity-temperature model on top of the original system's position-based PID controller, aiming to mitigate system positioning accuracy degradation caused by oil temperature rise. The corresponding framework is illustrated in FIGURE 4.3.

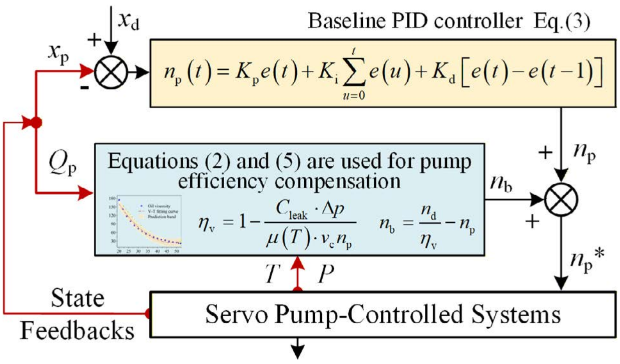

Figure 4.3. Pump Flow Compensation Strategy Based on the Platform-Fitted V-T Model

PID control is a classical method for servo pump-controlled systems. In the original system, position-tracking errors are constructed based on discretely sampled position signals, and the control law can be expressed as:

$$n(t)=K_p e(t)+K_i \sum_{u=0}^{t} e(u)+K_d\left[e(t)-e(t-1)\right] \tag{4.3}$$

where, e(t) denotes the tracking error, K_p, K_i, and K_d are the controller tuning parameters, and n(t) represents the controller output. The tuning parameters are set based on engineering practice and remain fixed.

Using the volumetric efficiency η_v estimated from the viscosity–temperature model, the compensation channel adjusts the pump command to offset the effects of leakage. Specifically, when the baseline PID controller requests a desired displacement x_d (or n_d), the compensation channel proportionally amplifies the speed command so that the actual flow Q_p closely matches the ideal demand $Q_d = n_d \cdot v_c$. The corresponding compensation flow Q_b can then be obtained as the reciprocal of the pump efficiency:

$$Q_b = Q_p^* - Q_p = \frac{Q_d}{\eta_v} - Q_p = \frac{Q_d \cdot \mu(T)\cdot v_c n_p}{\mu(T)\cdot v_c n_p - C_{leak}\cdot \Delta p} - Q_p \tag{4.4}$$

where Q_p* is the compensated flow, such that $Q_p = \eta_v \cdot Q_p^* = Q_d$.

Equivalently, the speed command of the servo motor can be scaled by the reciprocal of the efficiency to obtain the compensated speed n_b as:

$$n_b = n_p^* - n_p = \frac{n_d}{\eta_v} - n_p \tag{4.5}$$

where n_p* denotes the compensated rotational speed.

As illustrated in FIGURE 4.3, this channel functions as a parallel feedforward path, taking the baseline output n_p along with the current temperature T and pressure differential Δp as inputs to the compensation module, which outputs the gain-corrected command n_b. When η_v<1, n_b increases the pump speed appropriately to compensate for the flow deficit.

4.4. Performance Evaluation

To validate performance, multiple representative operating conditions were designed, under each of which 4,000 motion cycles were executed and data were collected for more than 4 hours in total. This design sufficiently captures the slow-varying characteristics of oil temperature during long-term operation, thereby verifying the general applicability and superiority of the platform and the proposed method under different conditions. The operating conditions were defined by varying actuator stroke and velocity, including a typical application condition with a 378 mm stroke, a short-stroke condition of 290 mm, a long-stroke condition of 406 mm, and a high-speed motion condition under the same long-stroke configuration. The detailed parameters of each condition are listed in TABLE 4.1, where the stroke and speed were set as percentages of the maximum hydraulic actuator stroke specified in the test standard [20]. Under the same temperature range, the tuning results obtained for different operating conditions are shown in FIGURE 4.4.

Table4.1. Detailed Experimental Operating Conditions

Scene	Distance (mm)	Velocity percentage	Purpose
1	378	80%	Frequent
2	190	70%	Short distance
3	406	70%	Long distance
4	406	99%	Speediness

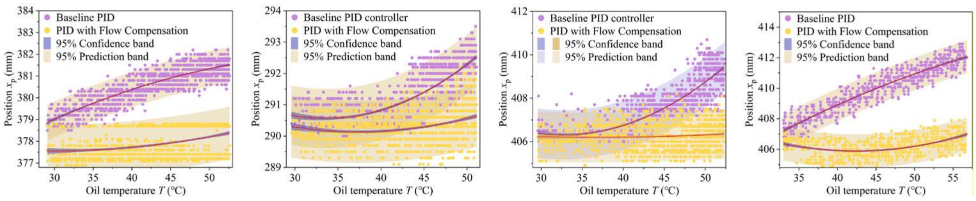

Figure4.4. Comparison of optimization effects for MCS. (a) Common operating condition. (b) Short-stroke condition. (c) Long-stroke condition. (d) High-speed condition

A cost function is constructed with the objective of minimizing the displacement tracking error to evaluate the optimization performance, and its magnitude of the real system under long-term operating conditions. The formulation is given as follows:

$$J = \sum_{k=1}^{N} \frac{\left(x_{\mathrm{p}} - x_{\mathrm{d}}\right)^2}{N} \tag{4.6}$$

where x_p denotes the actual terminal displacement of the system in the k-th experiment, and x_d represents the desired terminal displacement.

Table 4.2. The minimum cost values before and after optimization

Type	Common Operating	Short-Stroke	Long-Stroke	High-speed
J_b	7.61	2.32	3.75	18.33
J_c	0.45	0.37	0.41	0.44
R	94.1%	84.1%	89.1%	97.6%

With the minimization of the cost function J as the optimization objective, the minimum cost values corresponding to all tested configurations obtained from the displacement tracking error data are summarized in TABLE4.2. Compared with the cost function of the baseline system J_b, the optimized cost function J_c achieved using the digital platform is reduced by 94.1%, 84.1%, 89.1%, and 97.6%, respectively, demonstrating a significant improvement in system tracking accuracy.

5. CONCLUSION

This study addresses the issue of performance degradation in the MCS of IMM under temperature rise conditions by proposing a digital platform–supported approach for performance modelling and control optimization. By developing a platform that integrates data acquisition, simulation analysis, and data review, unified analysis of system operating data and model predictions is achieved. Focusing on the reduction of pump efficiency and deterioration of system positioning accuracy caused by temperature-dependent oil viscosity, the approach employs the digital platform for parameter mapping, inverse identification, and implicit indicator extraction to realize an engineering-oriented redefinition of pump leakage characteristics and explicitly incorporates the viscosity-temperature model into system modelling. On this basis, a pump flow compensation channel is introduced into the original position-based PID control structure to implement feedforward correction for the effects of oil temperature variation. Experimental results demonstrate that the proposed method significantly improves system positioning accuracy under multiple operating conditions, providing an effective interactive control optimization strategy for performance degradation driven by unmeasurable latent variables in EMH systems. Moreover, the proposed digital platform architecture and modelling methodology are designed with strong engineering scalability and system-level compatibility, enabling seamless alignment with both existing and emerging industrial digitalization standards. This provides a solid foundation for future integration with standardized communication frameworks, digital twin architectures, and collaborative simulation environments.

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